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1st Antonio Lanata
dept. Information Engineering
University of Florence
Florence, Italy
antonio.lanata@unifi.it

2nd Alberto Greco
Research Centre Piaggio
University of Pisa
Pisa, Italy
alberto.greco@unipi.it

3rd Stefano Di Modica
Research Centre Piaggio
University of Pisa
Pisa, Italy
stefano.dimodica@centropiaggio.unipi.it

4th Francesco Niccolini
Research Centre Piaggio
University of Pisa
Pisa, Italy
niccolinifr@gmail.com

5th Federico Vivaldi
dept. Chemistry and Ind. Chemistry
University of Pisa
City, Country
federicomaria.vivaldi@phd.unipi.it

5th Fabio Di Francesco
dept. Chemistry and Ind. Chemistry
University of Pisa
City, Country
fabio.difrancesco@unipi.it

6th Christian Tamantini
CREO Lab
Campus Bio-Medico
Rome, Italy
c.tamantini@unicampus.it

7th Francesca Cordella
CREO Lab
Campus Bio-Medico
Rome, Italy
f.cordella@unicampus.it

8th Loredana Zollo
CREO Lab
Campus Bio-Medico
Rome, Italy
L.Zollo@unicampus.it

9th Marco Di Rienzo
IRCCS Fond. Don C. Gnocchi
Milano, Italy
mdirienzo@dongnocchi.it

10th Carlo Massaroni
Meas. and Biomed. Instr. Lab
Campus Bio-Medico
Rome, Italy
c.massaroni@unicampus.it

11th Emiliano Schena
Meas. and Biomed. Instr. Lab
Campus Bio-Medico
Rome, Italy
E.Schena@unicampus.it

12th Mariasabrina di Sarto
dept. of Astr. Elect. Energy Eng.
Sapienza University of Rome
Rome, Italy
mariasabrina.sarto@uniroma1.it

13th Enzo Pasquale Scilingo
Research Centre Piaggio
University of Pisa
Pisa, Italy
e.scilingo@ing.unipi.it

***Abstract*—This study reports on a novel Smart-Fabric based wireless Body Area Sensor Network for assessing psychological and physiological work risk levels. The combination of smart-sensing fabrics advantages, high electronic miniaturization, and the latest machine learning enables the system to assess the risk level of the worker. The body area sensor network includes a smartphone, an artificial intelligence algorithm for risk assessment, and a set of sensor-nodes integrated into a textile substrate (i.e., activity detection, electrocardiogram (ECG), sweat rate, body temperature, and textile integrated respiration sensors). Preliminary and encouraging results are shown in terms of physiological signals and physical activity detection.**

***Index Terms*—Biomedical Signal Processing, Wireless Body Area Sensor Network, Smart Textile, Work Risk Assessment, Machine Learning, Mobile Platform.**

I. Introduction

The latter decades have seen fast development and diffusion of new technologies, which enable new ways of keeping safe conditions in the workplace and preventing injuries and death. Even though new typologies of risks for workers arise continuously, the achievements in high-level miniaturization, advanced sensors development, flexible electronics, and the internet of things (IoT) open to innovative strategies for preventing and mitigating the risks themselves. Recently, a rapid increase of both flexible and wearable electronics (e.g., bracelets, watches) for physiological signal monitoring as well as smart fabric capability has enabled system integration in many different types of clothes [1], [2]. Moreover, National Health System has highlighted how increase of workload can lead to occupational stress [3], affecting several work aspects such as staff turnover, job satisfaction, well-being, and the quality of work [4]. From a physiological point of view, stress induces a plethora of negative physiological states and psychological responses occurring in situations where individuals perceive threats on their well-being. For this reason, all evidence-based strategies able to recognize and mitigate these issues are crucial in the management of health in workplaces [5]. Furthermore, combining and integrating into smart fabrics wearable sensors and nanotechnologies, in an IoT context, open to innovative workplace accident prevention paradigm that focuses on the worker, his state of health, and the work-correlated stress [6]. This manuscript proposes a new Smart-Fabrics Wireless Body Area Sensor Network (SF-WBASN) for risk assessment in workplaces developed within the framework of the Italian National Funded Project Sense-Risc. The project aims at developing new smart clothes able to prevent physical and psychological injures of workers during their working-life through continuous risk level assessment.

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II. Sense-Risc Smart-Fabric Wireless Body Area Sensor Network(WBASN)

Sense-Risc FB-WBASN system consists of three parts: four autonomous sensor-nodes integrated into textile support; a mobile platform, and a machine learning algorithm running in a cloud (i.e., online). The four sensor-nodes are the respiration sensor, the ECG sensor, the sweat-rate sensor, and the inertial platform sensors. Each sensor includes a sensitive part connected to an electronic module for signal acquisition and Bluetooth communication (see fig. 3). Figures 1 and 2 show where sensor-nodes are located in the garment.

The mobile platform (i.e., smartphone), which has a central role in the system, as it is responsible for both sensor networks and (see fig.4) cloud management. Moreover, the online machine learning algorithm assesses the work risk level. The next sections will describe each part of the system in more detail.

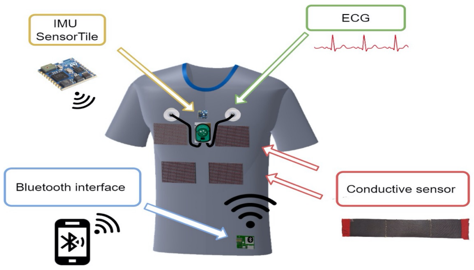

Fig. 1. Front View of the Sense-Risc SF-WBASN.

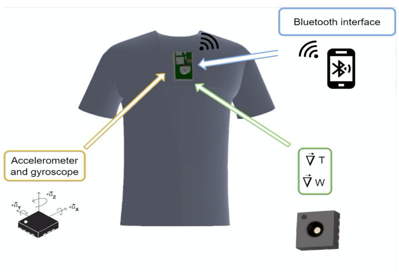

Fig. 2. Back View of the Sense-Risc SF-WBASN.

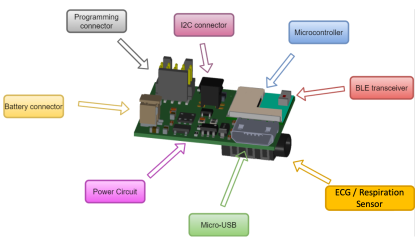

Fig. 3. Sensor board of the Sense-Risc SF-WBASN.

A. Central Platform

The Central Platform (CP) allows to use the system in different scenarios and also provides structured data to be correctly stored. It implements basic security rules, e.g., a user can read and write only his/her data while other custom rules can be further customized. CP comprises a Graphical Users Interface (GUI) and two modules (see fig.4). The GUI shows signals in Realtime, while the two modules send data to the cloud, receive the output of the online algorithm, and show the risk level. Moreover, CP interrogates all sensor-nodes following a predefined timeline and enables only the sensor-node that are relevant in the specific work scenarios. CP receives sensor-nodes data through the Bluetooth Low Energy modules (BLE) notification mechanism. The platform uses an ad-hoc protocol able to synchronize the nodes with an error < 1 ms. Of note, the Sense-Risc SF-WBASN P has been implemented within the Firebase platform: a web development platform owned by Google [7]. This allows the storage of relatively long raw signals inside a JSON-like document file through a noSQL database (Firestore Instance). It includes a machine learning tool (ML kit) to implement on-line custom TensorFlow Lite models (TFLM).

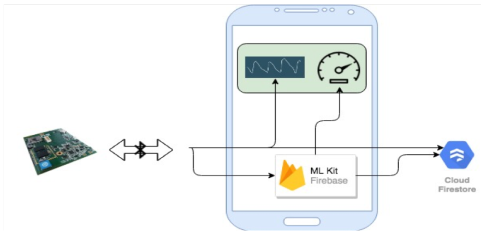

Fig. 4. Basic schema of the GUI, the risk model and the Cloud platform. The green area shows some of the information displayed in the GUI.

B. ECG Sensor

The ECG is monitored through a wearable wireless device, which is part of the SeisMote system (a wireless nodes network with sensors). Each node of the SeisMote system monitors a variety of signals: one-lead ECG, photoplethysmogram, 3D accelerations, 3D rotations (from gyroscope) (see fig. 5). The nodes can be directly positioned on the body by adhesive tapes, elastic straps, clips, or integrated into smart garments. During monitoring, data can be locally stored in the an internal memory card, or transmitted wireless to a computer for real-time visualization and analysis. The integration of one node of the SeisMote platform into the Sense-Risc WBASN for the ECG collection is foreseen for the SenseRisc project. ECG will be acquired at 200 Hz on 16 bits of accuracy, and the node will transmit data to the BAN receiver by the BLE protocol [8].

C. Respiration Sensor

Textile-conductive strain sensors are used to monitor respiratory activity. The sensing mechanism of these conductive sensors relies on the inherent design of the yarns. The application of a strain causes the rearrangement of the contact points between adjacent loops and a consequent variation of the electrical resistance. The relative change of the electrical resistance ($\frac{\Delta R}{R_0}$)is proportional to the applied strain (ϵ). The respiration sensors can be directly printed on the shirt itself

Fig. 5. The SeisMote system.

by a screen printing technique. The front-end electronics transforms sensor resistance variations in voltage outputs, which are either stored in a local memory or wirelessly streamed to a computer for real- time visualization and analysis. In Sense-Risc project, four sensors will be applied to thorax and abdomen for recording the respiratory activity (see Fig. 1).

D. Inertial Platform Sensor

ST Microelectronic SensorTile, which embeds magneto-inertial sensors LSM6DSM (3-axes accelerometer, 3-axes gyroscope) and LSM303AGR (3-axes accelerometer, 3-axes magnetometer), will be used to monitor the movement of the worker. This node can be directly placed on the garment by adhesive tapes or be integrated into the smart garments (see Figure .1). Data can be locally stored in the internal memory, or wirelessly transmitted.

E. Sweat-rate Sensor

The sweat-rate sensor is based on an open chamber approach and will be placed on the back of the garment (see Figure ig.2). It consists of a cylindrical structure embedding two temperature and humidity sensors at different heights from the skin. Once the sensor is put in place, a diffusive flow through the chamber starts due to insensible and sensible perspiration. The sweat rate can be calculated from the humidity gradient thanks to either the first Ficks law or calibration. Along the chamber axis, the Ficks law can be written as follows:

$$J = -D\frac{d\varphi}{dz} \tag{1}$$

where J is the diffusion flux $[kg/(m^2s)]$, i.e. the amount of water vapour flowing through a unit area during a unit time interval, D is the diffusion coefficient or diffusivity $[m^2/s]$, ϕ is concentration $[kg/m^3]$, and z is the distance from the skin $[m]$.

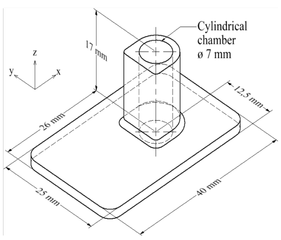

Fig. 6. Sweat and Temperature Sensor platform.

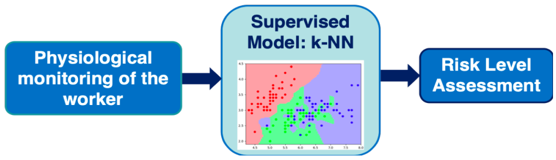

Fig. 7. Block scheme of the proposed classification system.

F. Risk level assessment

Data integration and interpretation has an essential role in the Sense-Risc project. Acquired data will be used to assess the work risk level during work activities. An ML approach will be adopted to estimate the risk level of the worker. A set of features will identify those parameters with the highest impact on the classification performance, and then a supervised algorithm will use the best subset of features to classify the risk level. In particular, a specific intelligent system will be implemented for each type activity. Currently, k nearest neighbours classifier (k-NN) is the candidate algorithm for Sense-Risc as it relies only on the training data without modelling decision boundaries that can lead to misclassification errors. The algorithm will be implemented within the third part platform Google Firebase to have an efficient ML model also able to satisfy privacy issues. Figure 7 shows a block scheme of the proposed approach. Data collection will be performed through simulations of risky situations to provide a reliable tool to classify and foresee risk levels. The risky situations will be labeled by using some indices already known in the literature, such as the ones introduced in [9] that can act as an estimation of the worker's heat stress.

III. Result

Since the project is at an early stage, we present only preliminary experimental results on data acquired from the already implemented sensor-nodes in laboratory settings. Furthermore, an intense working activity has been simulated to analyse the physiological signal changes that will be adopted as an input to the ML approach in estimating the workers risk level. Preliminary tests have been performed to compute both mechanical and electrical responses of the textile-conductive strain sensor. Figure 8 shows the sensor behaviour in terms of stress response and resistance changes to a series of sinusoidal mechanical deformation stimuli (100 cycles, amplitude 2 centimetres). Moreover, a set of preliminary experiments with the smart-fabrics-conductive strain sensor have been performed on one healthy volunteer for evaluating eupnoea (Figure 9, first subplot) and tachypnoea (Figure 9, second subplot). The voltage output (ΔV_{output}) decreases during the inspiratory phase while the expiratory phase causes an increase of ΔV_{output}. In the time domain, the time elapsed between two consecutive minimum peaks will allow calculating the breath-by-breath respiratory rate. Figure 10 shows an example of the IMU output (i.e., accelerometer and three-ax gyroscope) during a one-minute walk. Figure 11 shows the physiological signals acquired during light and intense physical activity (i.e. walking and running on a treadmill at a sustained speed) with

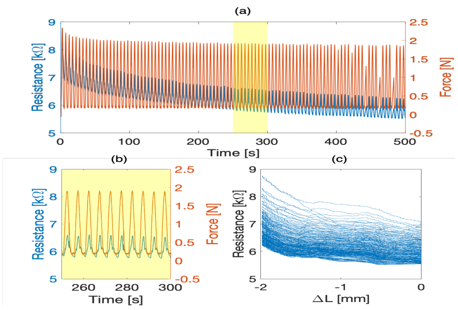

Fig. 8. (a):Stress and Resistance response to 100 mechanical stimuli cycles of over time; (b) Zoom-in of the Stress and Resistance response; (c):Resistance-Strain diagram of the smart-fabrics-conductive sensor

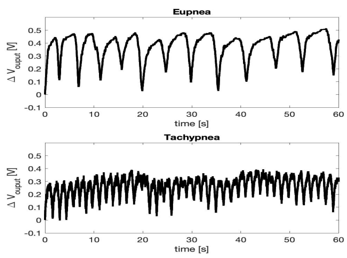

Fig. 9. Two examples of respiratory signals recorded by one respiration sensor during eupnoea (12 breaths/min) and tachypnoea (41 breaths/min).

commercial sensors such as Shimmer3GSR+, measuring the galvanic skin response, and BioHarness Zephyr, monitoring both heart and respiration rate. The black dashed vertical line represents the starting of the intense physical activity. There is an evident modification of the parameters according to the activity executed by the monitored user. An ML approach will be, therefore, a good solution to estimate such changes and classify risky situations.

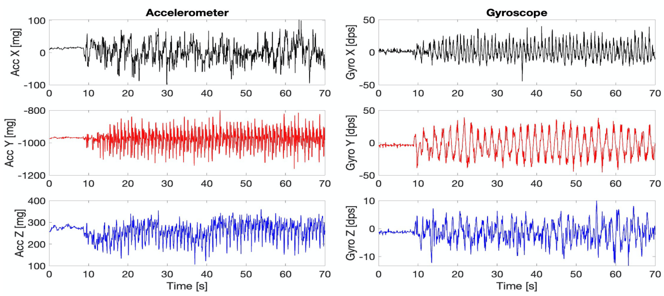

Fig. 10. Example IMU tri-axial accelerometer and gyroscope during 9[sec] of rest and 60[sec] of walking at 2Km/h.

IV. Conclusion and Discussion

This manuscript presented the implementation of the Sense-Risc SF-WBASN platform . Preliminary results are encouraging and show good accuracy of the sensor-nodes in detecting their specific information. The system exploit a network architecture based on Blue-tooth Real-Time communication mode (BRT), to obtain a continuous streaming of signals in BLE protocol versus the central platform and an efficient evaluation approach. The use of Google Firebase in CP and on-line ML implementation provides several benefits such as a reduction of the developing time, concise and effective software architecture, reduced boiler-plate code, data security, anonymity, and protection rules.

The final goal of the project , i.e., a continuously assessment of the work risk level in several work conditions, is highly ambitious. However, the achieved preliminary results and the level of the system implementation show a concrete possibility in reaching good final outcomes. Of note, all of the proposed implementation strategies and sensor-node functionalities need a careful validation in a large dataset acquired from workers in real setting scenarios.

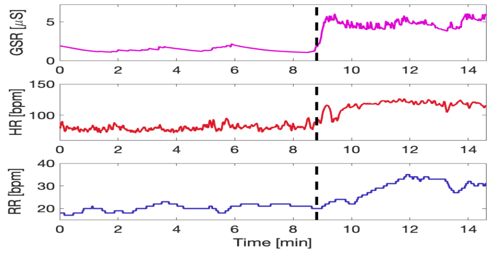

Fig. 11. Behaviour of the galvanic skin response, heart rate and respiration rate during a relaxing and an intense physical activity

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